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Do new research issues attract more citations? A comparison between 25 Scopus subject categories

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Abstract

Finding new ways to help researchers and administrators understand academic fields is an important task for information scientists. Given the importance of interdisciplinary research, it is essential to be aware of disciplinary differences in aspects of scholarship, such as the significance of recent changes in a field. This paper identifies potential changes in 25 subject categories through a term comparison of words in article titles, keywords and abstracts in 1 year compared to the previous 4 years. The scholarly influence of new research issues is indirectly assessed with a citation analysis of articles matching each trending term. While topic-related words dominate the top terms, style, national focus, and language changes are also evident. Thus, as reflected in Scopus, fields evolve along multiple dimensions. Moreover, while articles exploiting new issues are usually more cited in some fields, such as Organic Chemistry, they are usually less cited in others, including History. The possible causes of new issues being less cited include externally driven temporary factors, such as disease outbreaks, and internally driven temporary decisions, such as a deliberate emphasis on a single topic (e.g., through a journal special issue).

1 | INTRODUCTION

New and interdisciplinary researchers learning about a field need to discover its methods, topics and language style. Non-English speakers may also take specialist courses to learn academic writing styles for specific fields (Hyland & Shaw, 2016). For both reasons, it is important to be aware of disciplinary differences in how research fields and writing styles evolve. Systems to map the development of a field (e.g., Hu & Zhang, 2015) can help researchers, research funders and managers by identifying topic changes. Such systems are also used to predict future key research areas for the economy, sometimes called "technology foresight" (Miles, 2010). Technology foresight and science mapping algorithms may ignore non-topic changes in fields, such as the introduction of new methods or changes in academic writing styles (e.g., Bonn, Cho, & Um, 2018; Figuerola, Marco, & Pinto, 2017; Furrer, Thomas, & Goussevskaia, 2008; Mogre, Lindgreen, & Hingley, 2017). While this may not be critical for research managers or funders, it is unfortunate for researchers entering a new field because they may learn out-of-date styles.

There are many reasons why the nature and importance of research trends—other than topics—may vary between fields, necessitating deeper investigations into this issue. Academic fields evolve through human processes as well as by the logic of the underlying research objects, and there are substantial disciplinary differences in these (Becher & Trowler, 2001). One important dimension of difference is the extent to which there is agreement on the objects or methods of study (Whitley, 2000), with areas being inherently more conservative if new ideas attract conflicting reactions. These factors may explain why the rhetorical structures of disciplines vary, using different structures and formulations (Hyland, 2004). In addition, style changes sometimes evolve through informal practice (e.g., phasing out the indefinite pronoun "one", and either first or third person for methods descriptions; changes in syntactic complexity: Lu, Casal, & Liu, 2020), editorial guidelines (e.g., if the abstract must state "the context and purpose of the study": www.rhinologyonline.org/research.html), length restrictions (Hartley & Betts, 2009), field-wide guidelines for reporting types of study (e.g., Ghimire, Kyung, Kang, & Kim, 2012), influential academic style books (e.g., Flowerdew, 2015; Swales, 1990) or periodically updated rules, such as the American Psychological Association style guidelines (seventh edition in 2020). Finally, the types of contribution made to a field may evolve over time, such as the proportion of conceptual articles (Nunkoo, Thelwall, Ladsawut, & Goolaup, 2020), the balance of qualitative and quantitative articles (Reeves & Oh, 2017), and the way in which methods are reported, such as the statistical details (Chavalarias, Wallach, Li, & Ioannidis, 2016). Thus, fields evolve over time through multiple dimensions other than their topics.

This article uses a combination of existing methods for the dual tasks of identifying new research issues and assessing their likely longevity. Here, an issue is defined to *be any underlying change in a field that leads to linguistic changes in publications*. This encompasses style and methods changes as well as topic changes but not linguistic changes due to publisher mandated content (e.g., standard copyright statements or mandatory abstract headings). The method is based on word frequency comparisons applied to article titles, keywords and abstracts. For any set of articles from a field, it identifies a set of terms that occur statistically significantly more often in a given year than in the preceding 4 years. This set of terms can then be examined by a human expert to reject irrelevant matches and merge different words related to the same concept (e.g., West, Nile, virus). Applying the method to the current year gives a list of this year's new topics or other issues. Applying it to previous years in conjunction with citation analysis allows an assessment of the likelihood that new issues lead to sustained research or scholarly impact for a given field.

- RQ1: What types of underlying field changes can be detected by word frequency comparisons?
- RQ2: Are there disciplinary differences in the extent to which new issues are more cited?

2 | BACKGROUND

Although overall changes within research fields do not seem to have been investigated previously from a text analysis perspective, many previous studies have analyzed current or evolving research topics or research fronts. These are reviewed in this section to give context to the methods used for the new task of this article. All the methods described here assume that a topic is reflected in a set of distinctive and related words or citations: this assumption is not valid for stylistic changes and so none of the methods are directly applicable to the current task.

2.1 | Mapping research fronts

The standard method to map research fronts is to build a network of papers based on the citations between them and then to cluster the network, identifying sets of articles that tend to connect to each other more than to the rest of the network. The citation relationships can be co-citations, direct citations or bibliometric coupling, with the coupling approach being the best (Boyack & Klavans, 2010). If the method is applied to a set of documents from the current year, then the clusters are the currently researched topics. This detects research fronts in the sense of the currently researched areas of a field but does not identify what is new compared to previous years. Emerging research areas can be understood through time-based visualizations, however (Chen, 2006).

Network clustering has two relevant limitations. Clustering is inherently not robust in the sense that the solution depends on the algorithm used and can, in principle, be substantially changed by the addition of a single new data point or error. In addition, the clusters are not transparent in origins or meaning, since they are generated by a complex algorithm.

Another approach to map science and discover fields through clustering is to use word co-occurrences in the full text of sets of articles to detect themes through factor analysis, but this does not seem to work well (Leydesdorff, 1997). Network diagrams of word co-occurrences can also be used to detect themes visually in network diagrams (Leydesdorff & Welbers, 2011), but this does not provide statistical evidence of the results and is, so far, a small document set technique (e.g., 195 documents in the first figure of: Leydesdorff & Welbers, 2011). A larger-scale variant of co-word analysis is based on manually selecting high frequency keywords and then using clustering to identify underlying themes (selected words that tend to co-occur in the same documents) and network mapping to illustrate connections between themes (Hu & Zhang, 2015). This method reveals broad topics within a field but does not identify what is specifically new each year or easily show evolution over time. Topic modeling (Gal, Thijs, Glänzel, & Sipido, 2019) can also be used to reveal themes, but is not able to reveal fine-grained trends and, as with other forms of clustering, is inherently not robust.

Research topics can also be identified by analyzing citations to authors, such as with author co-citation analysis (White & Griffith, 1981). This is a broad-based approach, however, by focusing on authors rather than topics, and is more suitable for historical overviews of fields than for detecting current interests (because co-citations target older documents). Co-citations can be used to identify the relatively stable "intellectual base" behind a research front (Persson, 1994).

Clustering and mapping can be achieved with software such as SATI (Liu & Ye, 2012) or VOSViewer (Van Eck & Waltman, 2010). For example, VOSViewer can build networks based on citations, co-authorship and co-occurrence of words and phrases (www.vosviewer.com/features/highlights). Alternatively, fields can be characterized by analytical methods without software (Finlay, 2019; Mogre et al., 2017).

2.2 | Emerging research topics

Some citation and text-based methods have been developed that focus more closely on identifying emerging technologies, including research topics, from patents or research papers (Xu, Hao, An, Pang, & Li, 2020). Four partly conflicting criteria are sometimes used to characterize the importance of topics: novelty, growth, the existence of an emerging research community, and persistence (Porter, Garner, Carley, & Newman, 2019).

Burst detection algorithms can be used to detect new research areas from titles, keywords and abstracts. One approach extracted all sequences of 1–4 consecutive words, and identified those with the sharpest increase in frequency (Chen, 2006). A recent approach used a curated set of queries to extract a set of documents relevant to a preselected topic, extracted nouns and noun phrases from matching journal article titles and abstracts (not keywords), and mainly automatically and partly manually filtered out common general terms (because "users are put off to see noisy terms included") (Porter et al., 2019). The resulting terms were scored with a new Emergence Indicator (EI) when they meet four thresholds: occur in at least 3 years (persistence) and seven records; occur in less than 15% of records in an initial set of older records (novelty); occur at least twice as often in the current year than in the three previous years combined (growth); and excluding terms from articles with a common author. A heuristically designed score was then given to rank the terms, producing plausible lists of terms for three datasets applied to a seven-year period. This was characterized as a microlevel approach, identifying relatively fine-grained terms in comparison to research theme mapping approaches.

One study has applied citation analysis to emerging topics, showing that papers more related to emerging technology tend to be more cited, at least within Autonomous Vehicles, Nano-Enabled Drug Delivery, and Synthetic Biology (Kwon, Liu, Porter, & Youtie, 2019). This study normalized for paper age by counting citations per year (although citations accumulate nonlinearly: e.g., Finardi, 2014; Lachance & Larivière, 2014) and used a log transformation to reduce skewing. It also used regression with a wide range of control variables, such as journal impact factor, length, and first author country.

Statistical methods using the chi-squared distribution have been previously used to detect emerging topics within a time-stamped collection of non-academic texts, judging a noun phrase to be significant if it exceeds a heuristically determined significance threshold (Swan & Allan, 1999).

2.3 | Research histories

Research topics have also been investigated from a historical perspective rather than to detect new topics. One bibliometric approach to mapping the evolution of a topic is to identify highly cited works and then to track the relationship between them using citations. This can be achieved with the HistCite software (Garfield, 2009) and has the advantage that the maps produced are relatively simple, point to key papers, and show evolution. These maps can also be used to investigate processes behind knowledge building in science (e.g., Lucio-Arias & Leydesdorff, 2008).

3 | METHODS

To address the research questions, a simple procedure was designed to identify emerging themes through increases in the frequency of associated words. Unlike the algorithms reviewed above, the method does not assume that there are multiple related words or multiple related documents that are likely to be co-cited.

3.1 | Theme detection

The purpose of this procedure is to create a set of candidate terms reflecting likely new issues for given field and year. Human interpretation is needed (the final step) to convert these terms into issues because issues may be described by multi-word terms and a single issue may otherwise generate many new terms.

The algorithm uses a statistical significance test to identify sets of words used more in a year than in the previous 4 years, based on article titles, abstracts, or keywords. For example, if the term *data-sharing* occurred in 1.0% of Library and Information Science (LIS) articles from 2019 but 0.5% of LIS articles from 2015–18 then it would be a candidate term and tested for statistical significance. Since there are many candidate terms to test, a familywise testing procedure is used to (partially) guard against false positives. In more detail, the procedures are as follows. Instructions for applying this method with the free software Mozdeh are in the Appendix.

Step 1: Dataset. Obtain records for a set of journal articles from a field, such as from the Web of Science, Scopus, or Dimensions. Each record should include a title, abstract and keywords.

Step 2: Abstract parsing. Remove standardized phrases from abstracts, including copyright statements (e.g., "PsycINFO Database Record (c) 2007 APA, all rights reserved."), open access statements (e.g., "This open access article is distributed under a Creative Commons Attribution (CC-BY) 4.0 license."), implicit or explicit ownership statements (e.g., "Karger AG, Basel."), and mandatory keywords (e.g., "MAIN OUTCOMES AND MEASURES:"). Also remove bracketed references from abstracts, since these generate years as significant terms, and delete replicated publisher typos (e.g., "All rights reserved."). This method entails the generation of a large set of rules to remove undesired segments of text from the abstracts.

Step 3: Keyword counting. Convert each article into a list of constituent words from its title, abstract and keywords, ignoring duplicates (known as the bag of words approach in computational linguistics). Convert plurals to singular word forms by removing any trailing "s" (this is the only term normalization).

Step 4: Initial chi-square test. For each word in articles for the selected year y, count the number of matching articles from that year, m_y, and the number of matching articles from the previous four years m_4. Using the number of articles from the year n_y and the number from the previous four years n_4, conduct a 2×2 chi-square test for the statistical significance of the difference (i.e., whether m_y/n_y is statistically significantly different from m_4/n_4), and retain the p value. This test is valid because the null hypothesis for a 2×2 chi-square test with this data is that the two variables (article age and word frequency) are independent, so rejecting the null hypothesis translates to evidence that the relative word frequency (i.e., proportion of words per year) has changed over time.

Step 5: Familywise chi-square test. It is unsafe to run multiple simultaneous statistical significance tests since the likelihood of incorrectly rejecting at least one null hypothesis (i.e., falsely claiming a significant term) increases with the number of tests conducted. This can be remedied with a familywise error rate controlling procedure, such as Benjamini-Hochberg (Benjamini & Hochberg, 1995), which ensures that the overall error rate is fixed at a given level. The final stage is to apply this to select statistically significant terms based on their p-values. Essentially, the procedure increases the p-value threshold for statistical significance in a parsimonious manner to protect the overall false positive rate. For example, the test might increase the p-value threshold for each individual test from .05 to .0001 to preserve the overall threshold at $p = .05$.

Step 6: Significant term evaluation. Manually assess the cause of each statistically significant term, such as by reading a random set of article titles, abstracts or keywords containing it. Discard duplicate and irrelevant terms to produce a final list of emerging issues for the field.

The method above is similar to existing methods in technology foresight (e.g., Porter et al., 2019) in that terms are detected but focuses on single words and uses a statistical approach rather than heuristics to identify significant terms.

Statistical methods using the chi-squared distribution have been previously used to detect emerging topics within a time-stamped collection of news stories, judging a noun phrase to be significant if it falls over a heuristically determined significance threshold (Swan & Allan, 1999). The theme detection procedure above uses a more formal statistical method to control familywise error rates.

3.2 | Experiments

While the purpose of the theme detection procedure is to detect terms that might reflect new themes, it is helpful to demonstrate it on old topics so that the longer-term significance of the terms can be identified. The methods were therefore applied to historical data (journal articles 1996–2019) to assess whether they produced (a) any significant terms, (b) terms associated with different types of issue, (c) insightful terms, (d) issues of longer-term significance, and (e) results differing between fields.

A nonsystematic set of fields was chosen to cover a wide variety of areas: 25 Scopus narrow fields, out of the 331 non-empty narrow fields in Scopus (www.elsevier.com/solutions/scopus/how-scopus-works/content). Two contrasting psychology fields were included but otherwise the categories are all from different Scopus broad fields. The field names can be seen in the results.

The top term for each year and field (i.e., the term with the highest chi-square value) was manually classified by type by the first author to allow a discussion of the types of issues identified by the algorithm.

A convenient indicator of longer-term significance is a higher citation rate than average for the field, and so this was assessed. For the citation test, when a term was judged to be statistically significant in year *y* then the average citation count of all articles from that year matching the term was compared to the average citation count of the remaining articles from the field in that year. The average was calculated with the geometric mean because citation counts are skewed so the arithmetic mean is not appropriate (Thelwall, 2016). This approach is similar to that of a previous paper investigating the relationship between emerging technology and impact (Kwon et al., 2019), but uses a simple citation comparison rather than regression. Regression with journal impact factors as an independent variable is not relevant here because the focus is on changing citation impact for an issue, irrespective of the cause.

4 | RESULTS AND DISCUSSION

Detailed results and additional graphs are available in the supplementary material (https://doi.org/10.6084/m9.figshare.12115377). This section summarizes the key findings.

4.1 | Types of issue detected

The automatic theme detection method described above (steps 1–5) was applied to 25 selected Scopus narrow fields, extracting significant terms (words that occurred statistically significantly more often in a given year than in the previous 4 years) for all fields. It also detected statistically significant new terms for 2019 for all Scopus fields, with at least 2.5 new terms per year (median, since some fields had huge numbers of terms in individual years due to language, journal or news changes) for every field and with larger fields having more terms (Table 1, columns 1–5). Thus, despite the careful statistical procedure, the method does not reject all candidate terms.

The manual classification of the statistically significant terms (theme detection step 6) attributed a likely cause for the top term for each field and year (when there was one) to illustrate the types of issues detected by the method. The classification results are from only one coder, but the top terms in italic in the list below are presented as evidence that each theme occurred in the data. The following field-related issues generated top keywords in one or more fields in Table 1 (see also last column of the table). This list shows that factors other than new research topics can generate changes in fields, as reflected in the words used in article titles, abstracts and keywords.

- **Topics**: Terms related to topics occurred for all fields. These could either be directly describing a topic in a word (e.g., *terrorist*, *H1N1*, *pharmacoepidemiology*, *wn* [West Nile virus]) or through words within multi-word phrases (e.g., *expression* for gene expression, *nanotube* for carbon nanotubes, *translational* for translational medicine [in Transplantation]).
- **Methods**: Some words related to methods evolutions, such as the release of a new guideline or manual (e.g., *DSDM-5* in Clinical Psychology), or the increasing use of a different method (e.g., *simulation*) or software (e.g., the *ANSYS* package). Terms could be indirectly related (e.g., *PubMed* [for increasing use of systematic literature searches], *p*, *95* [for reporting statistical p-values or 95% confidence intervals]) or part of multi-word phrases (e.g., *Torrance* for the Torrance Verbal Test of Creative Thinking; *deep* for deep learning). Some measurement terms (e.g., *mA* in Mechanical Engineering) could reflect either methods or topics. Since Artificial Intelligence has a focus on methods, all terms describing machine learning algorithms were categorized as topics within this narrow field.
- **Style**: Some top terms were stylistic in the sense of relating to how research was reported rather than what research was done (e.g., *article* [in this article we…], *author* [In this article the author deals with…], *herein* [herein we report], *wise*). These could be second order effects of national differences in English phraseology. For example, the term *wise* seemed to be disproportionately used in one Indian journal within Library and Information Science. Changes may also reflect language evolution (e.g., *Lantinx*, a gender-neutral version of Latina/o was the top term in Education in 2019). The term *herein* occurred in multiple fields and experienced a dramatic rise in some, such as Mechanical

TABLE 1 Number of statistically significant terms by 25 Scopus narrow fields (1996–2019) with a five-year window. Bold percentages are above 50%

Scopus narrow field	Articles 1996–2019	Sig. terms 2000–19	Sig. terms 2019	Med. Sig. terms 2000–19	% terms more cited	% terms more cited to 2016 (med[a])	Non-topic terms[b]
Maternity Midw	14,954	92	10	3	46%	**100%**	TMSJ
Algebra Num Th	100,254	129	11	5	**74%**	**90%**	TS
Polymers Plastics	385,249	1,304	313	46	**76%**	**88%**	TS
Organic Chem	775,819	2,513	500	82.5	**72%**	**86%**	TMS
Oceanography	192,692	580	36	25.5	**74%**	**80%**	TM
Dermatology	159,810	386	67	13.5	**69%**	**78%**	TMSJ
Microbiology	301,573	1,115	179	42	**60%**	**77%**	TM
Fuel Technology	199,487	1,668	137	39.5	43%	**76%**	TMSN
Artificial Intel	203,458	754	172	16	**66%**	**75%**	TS
Transplantation	81,813	540	19	14.5	44%	**75%**	TMS
Stat Nonlin Phys	175,606	281	28	11	**70%**	**73%**	TMS
Mech Engineer	1,132,597	2026	253	79.5	**70%**	**73%**	TMSJ
Molecular Biol	993,389	3,142	433	137	**66%**	**70%**	TMS
Tourism	46,338	81	15	2.5	**53%**	**67%**	TS
Insect Science	162,545	251	18	13.5	**58%**	**64%**	TM
Epidemiology	126,130	545	67	21.5	**53%**	**61%**	TMS
Clinical Psych	179,008	464	67	23	**62%**	**54%**	TMSJ
Library & Info Sci	109,916	496	54	18	**53%**	**52%**	TMSJ
Social Psych	141,724	279	31	9.5	44%	50%	TMSJ
Glob Planet Chg	68,490	264	36	13.5	**52%**	48%	TMS
Miscellaneous	438,836	3,142	530	51	**56%**	33%	TMSJ
Vis & Perf Arts	48,890	182	38	6	32%	33%	TS
Education	484,127	1,028	106	28	31%	33%	TMJ
Gender Studies	40,646	94	15	4	43%	25%	TMSJ
History	152,223	328	24	12	35%	25%	TJ

[a]The median figure is the median of the yearly percentages of terms cited, ignoring years without significant terms. This is more robust against contributions from individual large journals added after 1999.
[b]Codes for issues influencing the top term for each year: T = topics; J = National journals; M = Methods; S = Style; N = News.

Engineering (Figure 2). This might reflect differing uses of English between countries or the convenience or standardization of the common phrase "herein we report" to introduce an article. For example, this phrase was used 106 times in *Journal of Alloys and Compounds* abstracts (often as the first three words). Some stylistic terms also reflect problem framing changes, such as the increased use of *challenging* and *outstanding* in Mechanical Engineering.

- **National journals/language**: The introduction of a non-English journal after 1999 could generate significant terms from common words in that language (e.g., *le* from the introduction of a French journal in Social Psychology). The rise of non-English journals to

Year	Top term	Year	Top term	Year	Top term	Year	Top term	Year	Top term
2000	metadata	2000	cosmic	2000	glass-transition	2000	physician-assisted	2000	
2001	learner	2001	wn	2001	glass-transition	2001	le	2001	cinematic
2002	wireless	2002	anthrax	2002	polym	2002	le	2002	author
2003	e-learning	2003	sar	2003	polym	2003	terrorist	2003	century
2004	oa	2004	sar	2004	clay	2004	body	2004	
2005	molecular	2005	jacc	2005	electrospun	2005	precariousness	2005	jung
2006	google	2006	preconception	2006	nanotube	2006	oxford	2006	torrance
2007	referendum	2007	expression	2007	nanotube	2007	jeune	2007	film
2008	er	2008	expression	2008	click	2008	god	2008	involve
2009	de	2009	h1n1	2009	click	2009	football	2009	guarini
2010	patron-driven	2010	h1n1	2010	cytotoxicity	2010	online	2010	design
2011	simulation	2011	h1n1	2011	graphene	2011	u	2011	warburg
2012	poster	2012	pubmed	2012	graphene	2012	cyberbullying	2012	football
2013	twitter	2013	pharmacoepidemiology	2013	c	2013	facebook	2013	zakopane
2014	altmetric	2014	aimed	2014	graphene	2014	nova	2014	parole
2015	dataset	2015	ebola	2015	herein	2015	mindfulness	2015	somatic
2016	big	2016	zika	2016	herein	2016	condomless	2016	coding
2017	electoral	2017	quickstat	2017	safeguard	2017	mage	2017	trump
2018	deep	2018	eskd	2018	herein	2018	que	2018	uso
2019	wise	2019	simulation	2019	wear	2019	p	2019	russian

FIGURE 1 The top term for each year for (left to right): Epidemiology; Library and Information Science; Polymers and Plastics; Social Psychology; Visual and Performing Arts. Timelines for all other fields and complete lists of significant words are in the supplementary materials (https://doi.org/10.6084/m9.figshare.12115377)

a level of credibility sufficient for Scopus indexing is important to a field, but not the individual common words in that language

- **National journals/regional terms**: The introduction of a national journal after 1999 could generate significant terms from proper nouns and adjectives related to that country (e.g., *Korean* from the introduction of the Korean Journal of Dermatology in Dermatology, or *Brazilian* from an increasing set of Brazilian journals in Education (Interface: Communication, Health, Education; Educacao e Sociedade; Educacao e Pesquisa; Ensaio; Cadernos de Pesquisa; Movimento; Revista Brasileira de Educacao; Revista Brasileira de Educacao Especial: Figure 2).

The following non-field issues also affected the results.

- **News**: News articles are sometimes indexed in Scopus as journal articles, generating large numbers of unique terms (e.g., company names) in a single year for uncited documents. This occurred for Fuel Technology for 1 year (756 terms, all associated with lower citation rates).
- **Typos**: Systematic typos created by optical character recognition can create new common words (e.g., "ami" for "and"), generating spurious significant terms for new journals.
- **Publisher standard texts**: Publisher-inserted texts, such as copyright or ownership statements caused words to be added that are not related to a field. The data cleaning stage ensured that none of these words were a top term for any field, but some occurred in the remaining statistically significant terms.

4.2 | Insightfulness of statistically significant terms

Although the algorithm part of the method (Steps 1–5) generates sets of statistically significant terms for each field, they are not all insightful. For practical purposes, it is therefore important to manually filter the terms to identify words that are part of multiword phrases and disambiguate the context, when necessary (Step 6). For example, a top term for Epidemiology was *WN*, representing the West Nile virus, and a top term for Polymers and Plastics was *click*, representing the click chemistry type of molecular reaction.

The LIS category is an example of a list needing extensive filtering. The 54 significant terms for LIS in 2019 were mostly due to the inclusion of a single national journal (884 articles from Library Philosophy and Practice from India in 2019, several based on local surveys), and the inclusion of an out-of-subject journal (Scientific Data, 342 matches in 2018). The terms are as follows, with the most useful issue words in bold: *wise* [more common in Indian academic English, for example, India ranks ninth overall for Scopus journal articles but third for Scopus journal articles containing "wise"]; ***neural***

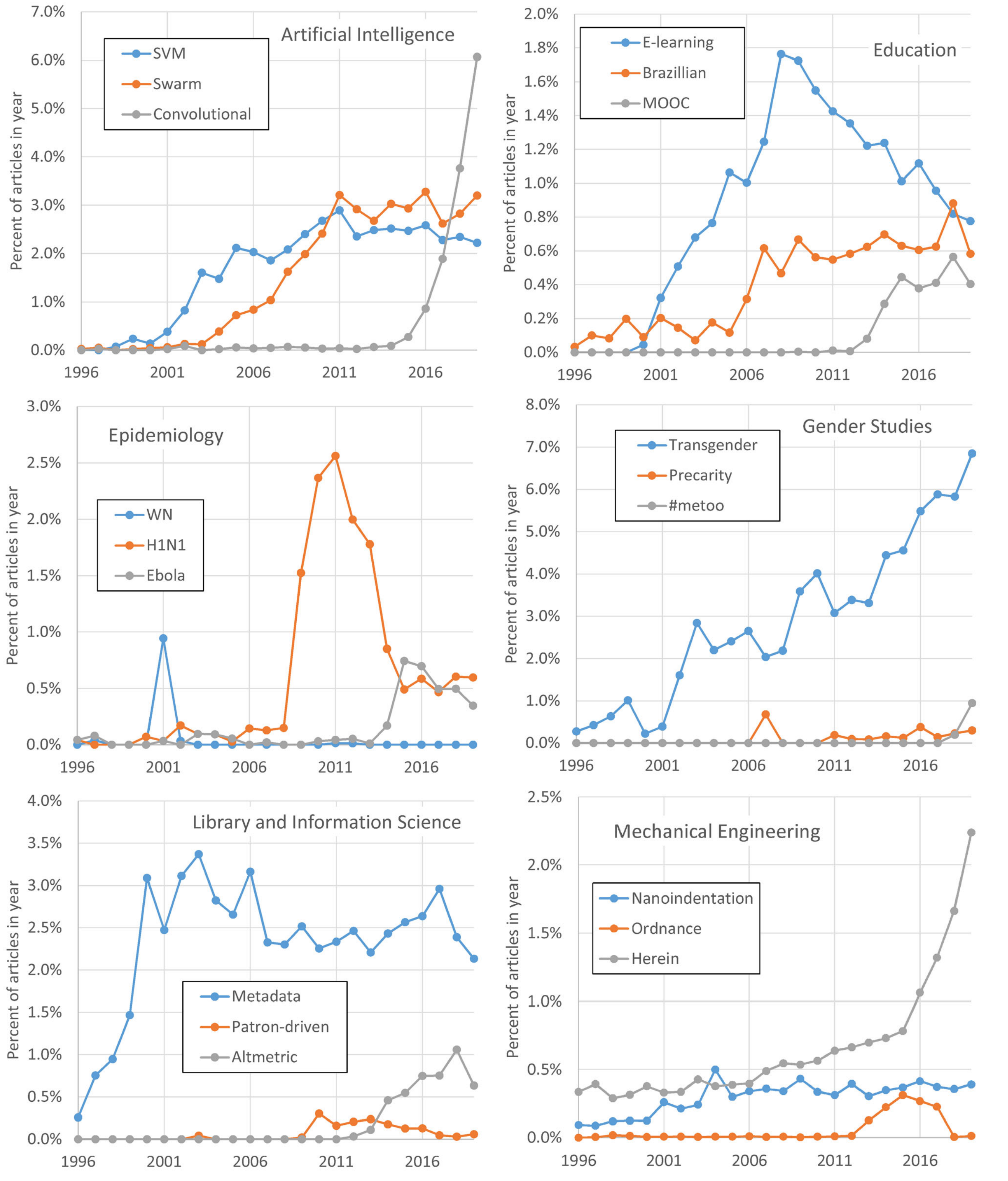

FIGURE 2 Trends in the relative frequency of three top terms for six fields. Sample sizes are in the online appendix

[networks]; *respondent*; *Nigeria*; *questionnaire*; *TamilNadu*; *N50* [contig N50, genomics term]; *India*; *revealed*; [Tamil] *Nadu*; ***ICT***; *Tamil*; ***sampling***; ***machine***; [Prof. Frantz] *Rowe*; ***blockchain***; [Prof.] *Frantz* [Rowe]; *Tirunelveli* [Tamil Nadu, India]; *utilization*; ***AI***; *collected*; *female*; *intention*; *percentage*; ***deep* [learning]**; ***IOT* [internet of things]**; ***dataset***; *contig* [contig N50, genomics term]; *Karnataka [India]*; *reformation*; *Alagappa* [University, India]; *male*; *2017*; *disinformation*; *behavior*; *equation*; *structural*; *total*; *aspect-based*; *busco* [Spanish];

descriptive; *filled*; *protein-coding*; *population*; *interview*; *size*; *internet*; *contribute*; *further*; *province*; *effect*; *mechanism*; *addiction*; *doubling*. Nevertheless, there are some general internet-related and artificial intelligence themes that are relevant to general LIS research (bold terms).

In contrast, the Mechanical Engineering terms seem more consistently useful, such as the top 20 from 2019: *herein*; [machine] *learning*; *convolutional* [neural network]; *dataset*; *cnn [convolutional neural network]*; *challenging*; *synergistic*; *high-performance*; *data-driven*; *lstm* [Long Short-Term Memory neural network]; *printing*; *outstanding*; *additively*; *printed*; *mah* [mAh]; *robotic*; *high-entropy*; *selective*; *ma* [mA]; *flame*. The stylistic terms *challenging* and *outstanding* may be particularly useful to know for researchers since their use in the field has grown exponentially throughout the period (e.g., from 0.1% to 1.4% for *challenging*).

Top terms can recur if their issue continues to expand over several years (Figure 1). Top term timelines may also give historical insights into the overall evolution of a field.

New issues may associate with short (e.g., *precarity* in Gender Studies) or sustained (e.g., *H1N1* in Epidemiology) bursts of activity, or may lead to long-term incorporation in a field and a stable level of higher use, such as *metadata* in Library and Information Science (Figure 2). Another pattern is a steadily increasing uptake of the issue, such as *transgender* in Gender Studies (Figure 2).

Field-specific phenomena can explain some features of the graphs. In Artificial Intelligence, convolutional neural networks have dramatically risen to eclipse two competing algorithms, Support Vector Machines and Swarm Intelligence, but the earlier two approaches continue to be used at an almost constant rate (Figure 2). This may reflect the nature of the field in that new algorithms need to be validated by benchmarking their performance against older algorithms. In contrast, in a medical field, a new cure might lead to the vanishing of older, less effective treatments. The trajectory of e-learning in Education suggests another phenomenon, a type of obliteration by incorporation (McCain, 2011; Zuckerman, 1987). Since electronic learning seems to be more important now than ever, perhaps the term e-learning is out of fashion, the concept is taken for granted enough that it does not need to be explicitly mentioned, or research about e-learning has narrowed down to use more specific terms (e.g., MOOC).

4.3 | The citation impact of articles mentioning new issues

There are dramatic differences between Scopus categories in the extent to which new issues tend to be more cited. The best measure of this is the median percentage more cited to 2016 column (Table 1, column 7), which ignores recent years (2017–19) due to short citation windows and takes the median of the yearly percentages of terms for which matching articles more cited. For example, in Algebraic Number Theory in 2000, for each statistically significant term, citation counts for articles matching that term were compared to citation counts for the remaining articles from Algebraic Number theory in 2000. The average over all terms in 2000 for Algebraic Number Theory was then calculated to give the year percentage. The median of all year percentages 2000–16 was then calculated, giving 90%. The median is better than the mean because anomalies (e.g., incorrectly indexed news articles) can cause extreme percentages for up to 3 years.

Although journal articles mentioning new issue terms tend to be more cited in 18 fields, they are less cited in six. In particular, new issues tend to be less cited in fields closer to the arts and humanities. The underlying cause may be that non-hierarchical subjects, such as arts, humanities and some social sciences, can discuss topical issues (or have special issue themes) but then immediately move on to a different focus, resulting in a low citation rate for previous year themes.

4.4 | Limitations and comparison with prior research

This study is limited by the ad-hoc selection of Scopus narrow categories and the lack of a formal evaluation for the usefulness of the terms found by the method. It is also limited by incomplete data cleaning, with only the top terms for each field and year being tested for unwanted causes.

While it was already known through extensive prior studies that new topics periodically emerge in some fields (Chen, 2006; Liu & Ye, 2012), and that new research areas can be more cited (Hu & Zhang, 2015; Porter et al., 2019), this study shows that the same is true for other research-related issues, including style, methods, and the emergence of national journals. Similarly, while the existence of fundamental disciplinary differences in research cultures (Becher & Trowler, 2001), intellectual strategies (Whitley, 2000) and writing styles (Hyland, 2004) were previously known, as well as the citation impact that novelty can have (Kwon et al., 2019), this study gives the first large scale evidence that the citation impact of novelty varies substantially between fields. The causes of this difference seem to be the non-hierarchical nature of the arts, humanities and some social sciences as well as, to some extent, the need to tackle temporary issues relevant to a field that emerge from the environment (e.g., H1N1).

In comparison to previous investigations (e.g., Porter et al., 2019) of new topics (which seem to dominate the issues in some of the fields), the method used here is relatively crude, relying on keywords rather than phrases and not clustering together similar concepts. Nevertheless, because of this it was able to identify non-topic factors evolving with fields, at least as captured by Scopus, such as styles (e.g., the terms *herein* and *challenging*), methods (e.g., *DSDM-5*, *simulation*), and terminologies (e.g., *precarity*). This heterogeneity creates additional challenges for new researchers seeking to understand the results (Step 6).

5 | CONCLUSIONS

The procedure introduced here has been shown to be capable of identifying new issues for a field from large collections of its journal articles (at least 5 years). The free software to apply the algorithm and the instructions below to use it are therefore a bibliometric contribution to other fields in terms of software to help new scholars to identify new issues. Some or all the information discovered by the method is likely to confirm the beliefs of experienced scholars in a field and offer them little value, except perhaps as a reminder or overview. Nevertheless, it may have value for new scholars or researchers within emerging research economies that lack experienced mentors until they themselves fill that role.

The results show that fields evolve not only as new topics emerge, but also as methods and writing styles change. Thus, researchers should be aware of the apparent need to be up to date in all three aspects of research. Identifying stylistic changes (e.g., increasing use of the word "challenging") may be particularly difficult.

This paper also shows that the citation impact of new issues varies substantially between fields, on average. This awareness may help interdisciplinary researchers seeking to understand the dynamics of a previously unknown field, especially if the interdisciplinary connection crosses the border between humanities-oriented research and other areas of scholarship. One simple consequence, for example, is that awareness of recent research trends is less important in the arts and humanities than elsewhere.

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APPENDIX: MOZDEH INSTRUCTIONS FOR DATA PROCESSING

- Download Mozdeh (mozdeh.wlv.ac.uk) to a Windows computer.
- Download the bibliometric data in plain text, tab-delimited format from the Web of Science, Scopus, Dimensions or another source and save it in a single folder.
- Start Mozdeh, enter a project name, click the Import Data button and enter 3 (bibliometric data) as the type. Select the folder containing the saved files and appropriate column numbers for the key data.
- After initial processing, Mozdeh will prompt for advanced processing options. Accept all the defaults except uncheck the "Use sentiment analysis" option to speed processing.
- When Mozdeh has finished, from the Advanced menu, select "Report 95% retweet confidence interval for Mine association significant terms matches vs. previous 4 years for all possible years."
- Load the file into a Spreadsheet to view the results. If the data is copied onto the supplementary material spreadsheet (on top of existing data, in cell A1: https://doi.org/10.6084/m9.figshare.12115377) then it will generate a summary timeline with the top keyword for each year and summary statistics (after adjusting columns L to R to match the length of the new data).